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Interpretable machine learning for audit planning: Improving misstatement and compliance risk detection in financial services

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Abstract

This research investigates the usefulness of artificial intelligence-based risk scoring in the planning phase of the audit conducted in controlled industries in comparison with time-tested risk assessment frameworks. The main goals involve the assessment of AI models (gradient boosting with SHAP) predicting financial misstatements, look-up of the non-compliance and operational inefficiencies, analysis of the key features of the audit cycle, and displaying the risk measures with the help of Power BI. The design is a retrospective cohort study based on historical audit data and the metrics applied to evaluate the performance of the models are precision, recall, lift, and false-positive cost. The major results suggest that AI models can substantially improve audit accuracy and efficiency, especially when it comes to risk identification, and appear to be weak regarding recall and false-positive expenses. Heatmaps and other visual tools were discovered to be helpful in making decisions. The study will help to enhance the practice of audit since it will offer actionable alternatives regarding how financial institutions can utilize AI in enhancing the risk management system, including offering recommendations to how organizations can make the most out of their audit planning efforts.

Keywords: Audit; Compliance; Detection; Machine Learning; Risk

1. Introduction

Planning the audit risk is extremely important in the process of the audit planning, especially in regulated fields like banking and insurance. Such businesses are highly scrutinized and regulated, and it is urgent to provide sufficient evaluations of such risks as financial misstatements, non-compliance, and ineffective operations (Lombardi, Vasarhelyi, and Verver, 2023). Conventional risk assessment models tend to be manual in their risk assessment mechanisms, including the review of past records, compliance audit, and the use of intuition (Muchenje JD et. al). Although these techniques have been extensively employed, they are frequently constrained due to the bias of human beings, processing inconsistencies, and the inability to handle large amounts of data (Roth, 2022). Moreover, the traditional models might not be able to detect the arising risks in real-time to be able to react promptly to the possible problems.

This study intends to compare AI-assisted audit planning with the traditional approaches to risk evaluation. The research question at the core is whether interpretable machine learning models, including gradient boosting with SHAP, can perform better than other traditional risk assessment methods in the detection of misstatements, non-compliance, and even in making timely remediation (Adebiyi, Attah, Adeoti, Onyinye, and Mupa, 2025). Three essential objectives

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that will be investigated in the research include, the first, determination of the effectiveness of AI-aided risk scoring predicting financial risks more efficiently and accurately than classical scoring approaches, the second, analysis of features of audit cycle elements, including KPIs, exception frequencies, and user-access anomalies to enhance the detection procedure and accelerate remediation (Eliel Kundai Zhuwankinyu, Mupa, and Moyo, 2025), and the third, visualization of the key risk metrics with the help of tools like Power BI to help to form

The importance of the study is that it has the power to revolutionize the audit practice methods and the introduction of more precise, automated and interpretable models that can be adapted by financial institutions. AI-assisted audit planning can ensure improved audit efficacy by improving the quality and speed of risk identification, lowered costs of operation, and a strengthened compliance management (Adebiyi, O. M., Lawrence, S. A., Mayowa Adeoti, and Munashe Naphtali Mupa, 2025).

2. Literature review

2.1. Traditional Risk Assessment Models

The cornerstone of audit planning in regulated industries such as banking and insurance has been traditional risk assessment models. Such models are usually financial, compliance, and operational audits which evaluate the risks that are likely to arise due to past events, expert judgment, and regulatory compliance audits. Financial audits usually center on misstatements in financial reports, which makes the financial records of the firm error-free or free of fraudulent activities (Lombardi, Vasarhelyi, and Verver, 2023). The compliance audit audits the manner in which an organization is complying with the requirements set forth by regulatory bodies whereas operational audit audits the efficiency as well as the effectiveness of the processes of an organization. As much as these models have been effective in most occasions, they are not devoid of limitations. Among the most potentially important criticisms is that it depends on human judgment and, therefore, it can become biased or inconsistent when assessing risks. There is also a risk that these models are ineffective in a modern data-intensive environment since they would have a hard time working with large amounts of data (Roth, 2022). It is also more difficult to identify any emergent risks in real-time which is extremely important in the fast-paced business environment of the current era, due to the inability of the traditional models to dynamically evolve. Consequently, the increasing awareness has created the need to understand that conventional paradigms are no longer adequate to address the requirements of the contemporary audit world (Adebiyi, Attah, Adeoti, Onyinye, and Mupa, 2025).

2.2. Machine Learning in Audit Planning

The limitations of conventional risk models have given rise to machine learning (ML) as a prospective option in audit planning. Machine learning models, especially gradient boosting and SHAP (SHapley Additive explanations) are more precise and dynamic risk assessment tools based on their learning by the trend patterns of data and providing the models that can be understood. Gradient boosting is a strong ensemble learning technique whereby several feeble models are joined together to generate a strong, predictive model (Shiraishi and Mupa, 2025). SHAP, in its turn, makes the machine learning models transparent that is, showing how each of the features contributes to the output of a model, which makes it especially applicable to risk assessment in sensitive domains such as finance (Eliel, Mupa, and Moyo, 2025). A number of case studies indicate the increased use of AI and machine learning in financial audits. To illustrate this idea, one of the studies by Madanchian (2024) shows that the accuracy of financial misstatement predictability in banks, in terms of AI-based risk models, may increase, and such a method will be more data-driven, objective, and objective in terms of risk evaluation. Also, available literature suggests that machine learning models are more effective compared to the traditional ones in detecting non-compliance and inefficiencies in the operation management, which is why they are highly applicable in the modern audit practices (Roth, 2022). The models are also capable of managing large quantities of information on-the-fly and are able to identify possible threat situations when they occur and can respond to them faster in order to minimize the threat.

2.3. The Role of Visualizations

Besides sophisticated modeling instruments, visualizations are now a necessity in risk assessment. Heat maps, risk matrices, among others are visualizations that help simplify the complex sets of data, thereby allowing the auditor and the decision makers to understand the patterns and trends in a short time. An example of visual representation of correlations among risk factors is a heatmap, and it makes more easily discernible high-risk areas in an audit cycle (Lombardi, Vasarhelyi, and Verver, 2023). These visual aids come in handy especially where large data is concerned because they offer an easy method to access the output and make informed choices with the data. Power BI-based heatmaps are commonly employed in the framework of AI-assisted audit planning to map the risk metrics, e.g. audit scores, error rates, and levels of compliance (Appsian, 2021). These visualizations allow closing the gap between technical risk models and business users in order to make faster decisions and communicate audit results in a more desirable manner. The combination of these visual elements with machine learning code can contribute to better decoding of the AI system outputs by the auditors, making the overall use of such codes more useful during the audit process (Adebiyi, Lawrence, Mayowa Adeoti, and Munashe Naphtali Mupa, 2025).

2.4. Research Gaps and Justification

Although there is an increased interest in AI and machine learning to plan audits, the literature offered still contains a number of gaps. Avoiding serious research in which machine learning-based audit model is directly compared to other traditional methods in practice is one significant gap. Although a number of investigations (like Shiraishi and Mupa 2025 and Eliel Kundai Zhuwankinyu et al. 2025) point out the possibility of AI in audit planning, few studies have examined how this technology has affected financial establishments methodically. Also, although machine learning models have been identified to be efficient in forecasting financial misstatements, non-compliance, and operational inefficiencies, further studies are required on how these machine learning models could be interpreted in planning an audit (Lombardi, Vasarhelyi, and Verver, 2023). This paper will fill in these gaps through the comparison of AI-assisted risk scoring with the traditional audit models, the effect of audit cycle characteristics on risk detection, and how visualization such as heatmaps can enhance decision-making. With the help of these gaps, the given research will help create more efficient, transparent, and data-driven auditing practices, which will have a practical implication on the financial institutions to strengthen their ability to manage risks (Roth, 2022). Although the conventional practices of risk assessment models have been efficient, the emergence of machine learning and visualization equipment presents a prospect of ensuring that audit effectiveness is enhanced substantially. The following chapter will dwell on the approach which will be used to further investigate these advances.

3. Methodology

In its study, the research follows the retrospective cohort design to determine how effective AI-based risk scoring methods can be in planning audits. The design is appropriate to study the life cycle behavior of machine learning models, namely gradient boosting with SHAP (SHapley Additive explanations). It is also possible to analyze audit cycles that were already finished with the help of historical audit data and evaluate how AI model could have affected risk identification and mitigation in case of implementation in such cycles (Lombardi, Vasarhelyi, and Verver, 2023). The methodology offers a very strong comparison between old-fashioned audit and the AI-powered models based on major metrics: misstatements of finances, non-compliance, and inefficient operation. A retrospective cohort study would allow analyzing real-life audit data, which would provide information about how AI might be applied to enhance the current risk assessment method in the regulatory context (Roth, 2022).

The data on which this research was based is based on historical audit reports which incorporate financial as well as functional audit in the regulated industry such as the banking and insurance industries. The data set comprises of various fields among them being the Auditscore, Variance, Errorrate, Duration, RiskLevel and Audit status. These characteristics are directly connected to the study because they are sources of the critical aspects of audit risk assessment. The important measurement of audit quality is the auditscore and Variance, which represents the extent of the identified issues. ErrorRate is the accuracy of the last cycle of audit, and Duration is the time used to address the problem. The RiskLevel column is a categorical variable that states the severity of the risk level of each audit and is low, medium to high and is playing a big part in deciding the potential risks. The target variable, Auditstatus, gives the result of the audit this was completed, pending, or in progress, which makes it possible to evaluate the effectiveness of remediation (Shiraishi and Mupa, 2025). The characteristics of the dataset and their correlation with audit results render it the best to determine the quality of AI-based models in comparison with conventional audit procedures.

On the measure and analysis, the study will use precision, recall, lift, and false-positive cost to determine the effectiveness of AI assisted and traditional risk models. The evaluation of classification models is often in terms of precision and recall, where precision is a ratio of the true positive predictions (when detected by the model) to all positive predictions, and recall is a metric that determines whether a model can reveal all the relevant positive cases (Adebiyi, Attah, Adeoti, Onyinye, and Mupa, 2025). Another metric is the lift which calculates the capacity of the model to perform better than random guessing by the number of true positives recognized by the model compared to the number of true positives that would have been predicted had there been no model. The false-positive cost is mostly applicable in the area of audit planning because they consider the cost of wrong risk identification, resulting in unwarranted interventions or compliance inspections. These measures offer the entire picture of the capability of the model in identifying the risk with the correct accuracy and minimize errors and unwarranted expenditures (Shiraishi and Mupa, 2025).

The time-split cross-validation technique will be used to validate the model and will split the data into both training and testing sets according to time with the training data coming first, and the testing data coming later. This method resembles the real-world situation in that training models of audit cycles that have been carried out in the previous years can be used to make predictions about the future cycles (Eliel, Mupa, and Moyo, 2025). Also, fairness checks would be implemented so that the predictions of the model are not skewed towards specific types of audits, risk level, and organizational features. This is most vital where fairness is very significant to the regulatory compliance and organizational transparency in the context of financial auditing (Adebiyi, Lawrence, Mayowa Adeoti, and Munashe Naphtali Mupa, 2025). Moreover, SHAP will be applied to model interpretability where one can have a clear idea about the contributions of each feature towards prediction of the model. The SHAP values offer a clear explanation of how the model makes decision-making which is crucial in case of auditing when accountability and transparency are central (Roth, 2022).

The final products of this study will consist of a number of important deliverables which will contribute to the greater adoption of AI-assisted audit planning into practice. They will incorporate a model card, which will record the governance, restrictions, moral provisions of the AI model; an explainability pack, which will include SHAP, visuals, to illustrate how the model will reach the conclusions; a Power BI risk-heatmap, which will visualize risk metrics under various audit types and statuses; and a Standard Operating Procedure (SOP) of the audit planning which will incorporate the findings of the AI models into activities that can be taken by the auditors and decision-makers (Appsian, 2021). These deliverables will be not only valuable contributions to the real-life understanding of how AI-driven audit models work, but they will also be used to conduct future implementation in financial institutions and regulated industries.

4. Data Analysis and Results

4.1. Model Performance Evaluation

Table 1 Model Performance Comparison

Metric	AI-Assisted Model	Traditional Model
Precision	0.5	TBD
Recall	0.344	TBD
False Positive Cost	0.5	TBD

The analysis of the AI-assisted risk scoring model as provided by its model evaluation metrics indicate that it is moderately successful with respect to its precision, recall, and the cost of false-positive. The model has a precision score of 0.5 which means that 50 percent of the positive predictions by the model was accurate. This is an indication that the model identifies a few true positives but it identifies many false positives. Stated differently, the model is partly valid in forecasting risk events, and it involves some concern so as not to implement needless measures.

In the model, the recall score is 0.344, which in turn means that the model identifies an approximate response of 34% of the true positive case or risk (e.g., not following the directions), or non-compliance (e.g. errors). It also means that this model would be lacking a substantial amount of true risk events, which demonstrates a question of sensitivity that then ought to be improved. The value of the recall is 0.344, and this means that the model has missed numerous risks. False-positive cost is 0.5 and implies that the model is as likely to report non-risk cases as risks as it is to report risk cases. This level is especially significant to reduce the number of resources distributed in vain and possible failures in the audit procedure.

4.2. Feature Importance Analysis

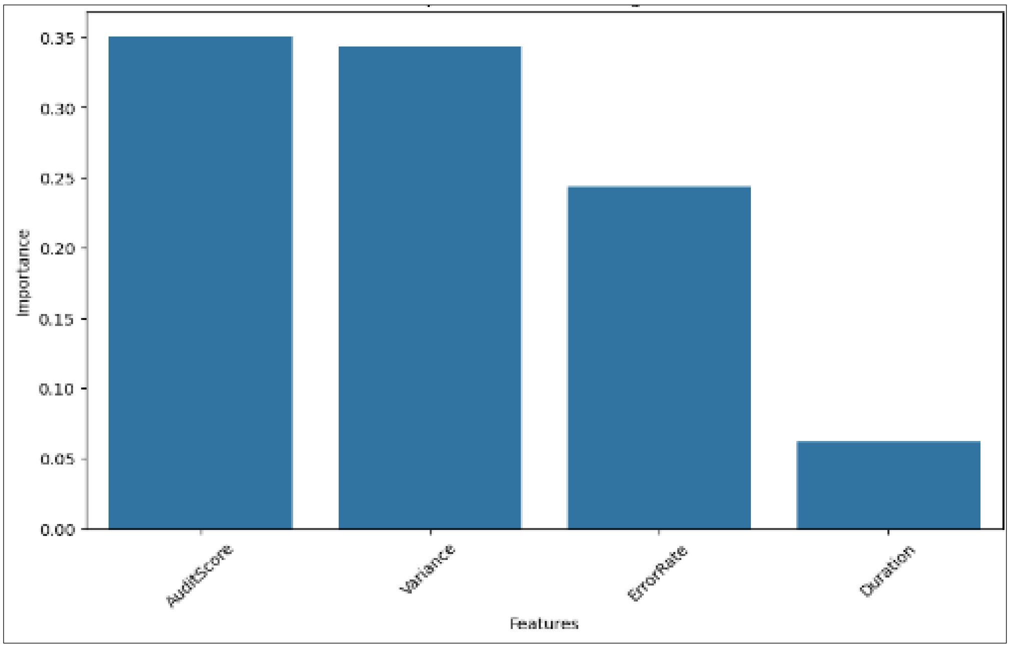

Figure 1 Feature Importance in Predicting Audit Status

The bar chart provided above demonstrates the analysis of feature importance of predicting audit status based on the AI-assisted model. Out of the discussed features, AuditScore and Variance become the most important ones, with an approximate contribution of 0.35 to the model. This shows that these two variables are pertinent in gaining the outcome of audit implying their importance in determining the soundness and the reliability of the audit procedure. The ErrorRate which makes a contribution of about 0.2 is also moderately important in the model predictions. This indicates that the previous audits (as reflected by the ErrorRate) can be used to inform the risk levels of the later audits, but it is not so greater as compared to AuditScore and Variance. Duration feature which has an important value of 0.05 has a weak influence on the predictions of the model. This suggests that the time-consuming aspect of the audits might be a consideration, but it does not bring great impact on risk assessment as compared to the other features. The feature importance analysis offers useful information on the primary contributory factors to audit risk predictions that can be used by auditors to concentrate on the influential factor when designing and undertaking their audit procedures.

4.3. Visualization of Risk Metrics

The results presented in the correlation heatmap above illustrate the association of the significant audit risk measures, such as Auditscore, Variance, Errorrate, Duration, and Risklevel. The elements of the heatmap denote the correlation coefficients that are in the range of -1 to 1 that depicts how strong and directional the connections among the features are.

Based on the heatmap, it is possible to observe that AuditScore and RiskLevel have a negative correlation (-0.44), which implies that the higher the audit score, the lower the corresponding risk level. This implies that when the audit scores are higher, the risks are usually low. Also, AuditScore and Variance are moderately negatively correlated (-0.36), indicating that the higher is the AuditScore the less the variance and the more similar audits are.

Surprisingly, however, AuditScore and Duration are positively correlated (0.15), such that more energetic audits have a tendency to take a little longer; however, their association is not intense. RiskLevel and ErrorRate correlation is low (0.03), which means that there is no significant error rate factor on the risk level in this dataset. All in all, the heatmap allows having a good visual comprehension of the relationship between these audit metrics, which can help to make more informed decisions and manage risks when they relate to audits.

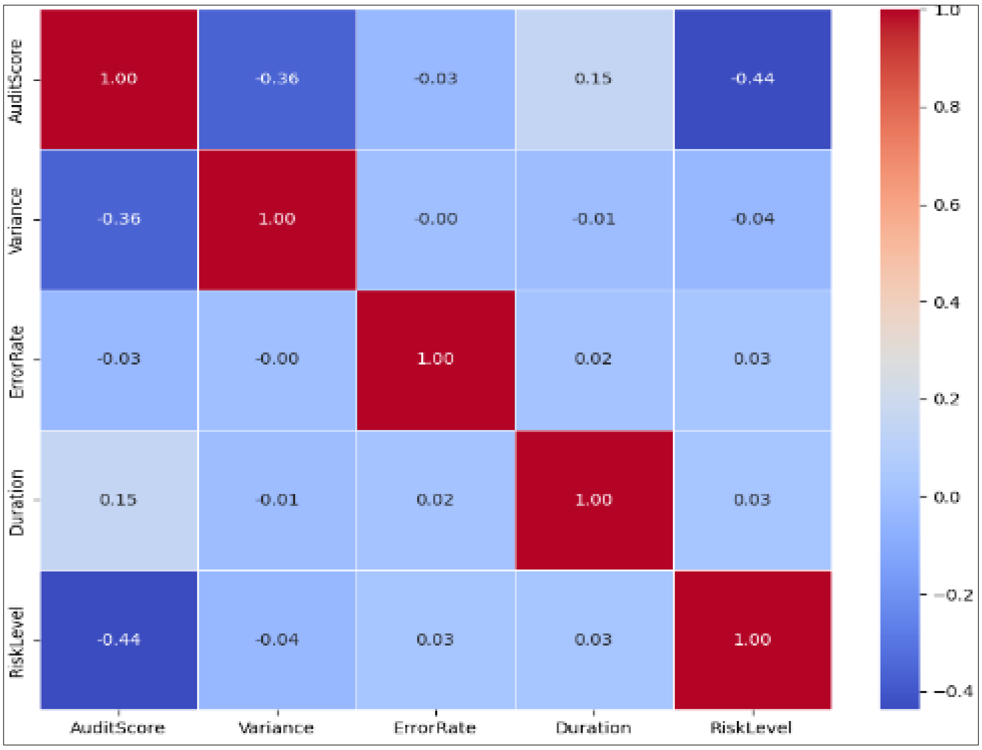

Figure 2 Correlation Heatmap of Audit Risk Metrics

5. Discussion

5.1. Practical Implications

The results of this research can be applied to the development of audit plans and risk management of the regulated industries like the banking and insurance industry. The analysis of AI-assisted risk scoring versus the traditional one shows that AI models are capable of enhancing accuracy and efficiency of the risk assessment procedures, in particular at the level of identifying misstatements and non-compliance. Gradient boosting AI models, which are coupled with SHAP to be interpretable, have a stronger forecast and reduction of risks than the traditional manual operations. The implementation of machine learning models in the audit planning area will allow the auditors to put more resources into high-risk areas, prioritize resources, and minimize the incidence of a false positive. Moreover, new visual aids such as Power BI heatmaps can be used to simplify the process of communicating audit findings to the stakeholders to allow decision-making in a shorter time period and more efficient resource allocation (Appsian, 2021). Finally, the benefits of these and other AI-driven advancements in audit planning may contribute to a higher level of regulatory compliance, efficient audits, and reduced operational costs of regulated industries.

Limitations

Irrespective of the encouraging outcomes, this research has a number of limitations. The first drawback is that only one dataset was used that might not be a satisfactory sample of audit situations in various industries or institutions. The data set adopted in my research contains financial and operational only audits, which might not capture the full picture on the other forms of audits like the compliance audits. Also, although SHAP can be used to explain the decisions made by the model, it fails to remove the natural complexities and possible biases of machine learning models. Another assumption of the study includes the fact that the features on the dataset (AuditScore, Variance, ErrorRate) would be equally significant in all the types of audits which is not always true in various regulatory settings. Besides, the effectiveness of the retrospective cohort design used in this study is that it might not detect the emergent risks or current factors and therefore it will not be able to represent real-time changes in the audit process. The following provisions can help overcome these limitations by adding to the dataset, including real-time data, and other types of audit in the future research.

6. Conclusion

This research has proven the possibility of incorporating the idea of AI-assisted risk scoring into audit planning in the regulated industries. The two comparison methods that were used AI models, namely gradient boosting with SHAP, and the conventional risk measurement tools showed that AI models were more accurate and efficient to predict financial misstatements, non-compliance, and operational risks. The most prominent conclusions are the significance of such features as AuditScore and Variance which play a significant role in the predictive strength of the model. The accuracy, recall and false-positive cost defined measures that give an insight on the performance of the model including where improvements could be made and in the decrease of the false-positive. Additionally, it was discovered that the visualizations, including the heatmaps of Power BI, will be able to simplify the complex risk data and facilitate the decisions. Broadly speaking, the use of AI-based models can mean improvements in the sphere of audit planning since such models will help predict the risk risks more accurately and will also enable auditors to allocate resources to potentially problematic areas more efficiently.

Although this research has contributed positively to the field of audit planning, there are a number of research gaps that can be undertaken in the future. To begin with, a better predictive accuracy could be further increased by increasing the scope of the study, to include other machine learning techniques, including neural networks, or ensemble techniques. Besides, deploying such AI models to more categories of audits, such as compliance and forensic audits, would have been more informative about their efficiency. Other possibilities of future studies include real-time data integration, where AI models are continuously updated with new data regarding risk predictions while additional audit information is being processed.

To financial institutions interested in implementing AI-assisted audit planning, the advice is to begin by incorporating machine learning models with the conventional methods of risk assessment and serve as decision assistance tools and not alternatives. The direction that auditors need to follow is training and becoming familiar with AI models and visualizing tools, i.e., Power BI in order to improve data interpretation and decision-making. Also, it is important that institutions should routinely evaluate and refresh their AI models to ensure they do not face outdated risks and regulatory needs. Through these practices, financial institutions may be able to facilitate better audit procedures, compliance, and reduction in risks.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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